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MaxEnt modeling for predicting suitable habitats and identifying the effects of climate change on a threatened species, *Daphne mucronata*, in central Iran

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A B S T R A C T

Climate changes pose serious challenges to the persistence of plant species, especially those with narrow habitats. Failure to adopt timely measures would lead to the permanent loss of valuable endangered species. This study used maximum entropy to predict the geographical distribution of a medicinal and vulnerable plant species, *Daphne mucronata Royle*, under current and future climatic conditions (A2a/HadCM3) in central Iran. A total of 100 locations with the species occurrence were recorded. Three topographic variables (slope, elevation, and aspect) and 19 bioclimatic variables derived from monthly data (spatial resolution = 1 km) were used in the modeling process. The results showed that *D. mucronata* distribution was largely affected by elevation, annual precipitation, and precipitation of coldest quarter. According to species response curves, this species preferred habitats with mean precipitation of coldest quarter from 120 to 140 mm, annual precipitation of 240–280 mm, and elevation more than 2600 m above sea level. The climate change projection (A2a/HadCM3) indicated that by 2030 and 2080, *D. mucronata* would disappear in sites located below 2000 m, remain unchanged in elevations more than 3000 m, and undergo a drastic change in sites located at 2000–3000 m above sea level. This information is essential for conservation planners and rangeland managers who work on protecting the species from extinction. A similar approach can be adopted to identify sites with high extinction probability of endangered species and to protect susceptible habitats from the effects of climate change and future modifications.

1. Introduction

Species distribution modeling (SDM) is becoming increasingly popular in ecological applications (Elith et al., 2006; Peterson, 2006). SDM can be defined as the predicted distribution of species across the landscape based on the relationship between the species occurrence and environmental variables (Guisan et al., 2002). Climate, topography, soil characteristics, land use, and biological interactions have been identified as the main determinants of species distribution in various geographical scales (Ellenberg, 1988; Walter, 1985; Woodward, 1987). Geographic information systems (GIS) permit climatic, ecological, and topographical variables to be rapidly and directly associated with points of species occurrence at the landscape scale. They thus enable environmental and land managers to predict species distribution in the context of biodiversity analysis (Anderson et al., 2002; Illoldi-Rangel et al., 2004; Peterson, 2006).

Since the identification of physiological requirements of plant species is difficult, complicated, and costly, details of species' dynamic responses to environmental changes have been only studied in a limited number of species. Correlative models are considered as an alternative approach to evaluate the possible consequences of a changing environment on geographical distribution of plant species (Woodward and Cramer, 1996).

Based on the types of response variables, species distribution models can be classified into two groups: those using presence-absence data (GLM, GAM, CART) and those using presence only data (ENFA, DOMAIN, GARP, MaxEnt) (Phillips et al., 2006; Soberon and Peterson, 2005).

MaxEnt is a machine learning model which estimates a target probability distribution by calculating the probability distribution of maximum entropy (Phillips et al., 2006). Species' sites of occurrence are regarded as appropriate places to meet species' ecological requirements. Although MaxEnt offers acceptable results even with a limited available sample size (Phillips et al., 2006), it requires an appropriate distribution of occurrence points in the ecological space rather than the geographical space (Kadmon et al., 2003; Thuiller et al., 2004). MaxEnt is also capable of projecting shifts in species distribution under various climate change scenarios (Garcia et al., 2013; Pearson and Dawson, 2003; Remya et al., 2015; Yang et al., 2013). MaxEnt is a preferable method from all possible approaches working with “presence data only” because detecting and

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Fig. 1. *Daphne mucronata Royle* is a medicinal and vulnerable shrub species in Central Iran.

collecting absence data is difficult and rarely available (Elith et al., 2011; Phillips et al., 2006) and its model output is continuous (maximum likelihood estimate of relative probability of presence) rather than deterministic role (e.g. GARP) (Arnold et al., 2014).

The International Panel of Climate Change (IPCC) has predicted that average temperature will increase up to 5.8 °C by the end of this century (IPCC, 2001). Since some species have already responded to a temperature increase of 0.6 °C during the past century, more substantial effects on species and ecosystems are expected to occur in the future (Root et al., 2003). Phenological and range shifts induced by climate change are inevitable and many researchers have thus tried to identify and prioritize “species at risk” or “endangered species” (Jones et al., 2013).

Daphne mucronata Royle is a medicinal and vulnerable shrub species from the Thymelaeaceae family (Fig. 1). It is distributed in the ecotone zone between semi-Steppe and arid forests in central Iran. The canopy cover of this species serves as nests protecting birds' eggs from predators. This valuable and unpalatable species can also prevent erosion. Moreover, *D. mucronata* has been traditionally used to treat skin disorders (Avicenna, 1997). However, a remarkable decline in this species, along with *Astragalus adscendens* and *Quercus brantii*, has been reported (Hu et al., 2015).

Climate changes pose serious challenges to the persistence of plant species, especially those with narrow habitat, and force them to either adapt to the new conditions or shift their geographical distribution (McLachlan et al., 2005; Parmesan, 2006; Root and Schneider, 2006). Restoration goals should hence be promptly adjusted with climate changes as any delay would lead to the loss of invaluable endangered species (Jackson and Hobbs, 2009). This study mainly focused on predicting the geographical distribution of *D. mucronata* under current and future climatic conditions (A2a/HadCM3) in central Iran using MaxEnt. The developed model would play a key role in nature conservation planning for the selected species and facilitate the reintroduction, rehabilitation, and recovery of the species.

2. Materials and methods

2.1. Study area

The study area is located in central Iran (Isfahan Province, 31°26′-34°30′ N, 49°30′-55°50′ E) and covered an area of 107,027 km^2 (Fig. 2). Moving from east to west, the altitude (ranging from < 500 m to > 4000 m) and precipitation (60–740 mm) increase, but the average temperature decreases from 22 °C to 4 °C. According to the Gaussen's xerothermic index (1952), several bioclimatic zones could be identified in the study area, i.e. semi-arid and arid zones covered the northern and eastern areas while cold xeric and cold Steppe covered the west and southwest areas (Bagherzadeh, 2000).

According to the IPCC database, under a climate change scenario (A2a/HadCM3), Isfahan will encounter 0.5–2.0 °C (mean: 1.4 °C) and 3.0–6.0 °C (mean 4.5 °C) increases in temperature by 2030 and 2080, respectively. Moreover, 39 and 55 mm reductions in the mean annual precipitation are expected by 2030 and 2080, respectively. As a coupled atmosphere-ocean global climate model (GCM), HadCM3 is commonly used in climate change assessments. A2a assumes a highly heterogeneous future world with regionally oriented economies with high population growth rate, land use changes, increased energy use, and slow technological change (Samadi et al., 2010).

2.2. Species occurrence and environmental data

A total of 100 locations with *D. macronata* occurrence were recorded during 2013–2014 using the Global Positioning System (GPS) and field surveys (Fig. 2). Bioclimatic variables were derived from monthly data related to 1950–2000 (Hijmans et al., 2005). The data had a spatial resolution of 30 s (ca. 1 km) and were downloaded from WorldClim dataset (www.worldclim.org). Future climate data including A2a emission scenario HadCM3 model of 2030 and 2080 were obtained from the climate data archive of the Consultative Group on International Agricultural Research (CGIAR)'s Research Program on Climate Change, Agriculture and Food Security (CCAFS) (http://ccafsclimate.org). These future climate projections were based on the Fourth Assessment Report of the IPCC and were calibrated and statistically downscaled using the data for ‘current’ conditions. Overall, 19 bioclimatic variables (Bio1–Bio19) and three topographic variables (slope, elevation, and aspect) were used to determine the variables with the greatest effects on *D. mucronata* distribution (Table 1). The bioclimatic variables (Bio1–Bio19) represented annual trends (e.g. the annual precipitation and mean annual temperature), seasonality (e.g. the annual range of precipitation and temperature), and limiting or extreme environmental factors (e.g. the temperature of the warmest and coldest months and precipitation during the dry and wet quarters). The digital elevation model was used to generate slope and aspect map using ARC GIS software version 9.3. Bioclimatic variables were reduced to fewer variables for the modeling after examining cross-correlations among the variables to account for multicollinearity (Elith et al., 2011; Khanum et al., 2013; Stohlgren et al., 2011). We used $|r| > 0.8$ as a cut-off threshold to determine and exclude highly correlated variables (Table 2).

2.3. Maximum entropy modeling

MaxEnt is a freely available software categorized as a profile model (only presence data). It employs the maximum entropy algorithm and species occurrence to predict the probability of species occurrence in areas with unknown occurrence (Elith et al., 2006; Ortega-Huerta and Peterson, 2008; Phillips et al., 2006). This method is not sensitive to sample size and can generate species response curves in relation to environmental factors (Khanum et al., 2013).

Species occurrence data were divided into training set (70% of total occurrence records) for model calibration and test set (30% of total occurrence records) for model evaluation. All environmental factors were converted to ASCII raster grids with the same pixel size (30 arc sec) and projection (decimal degrees). Linear, quadratic, and hinge

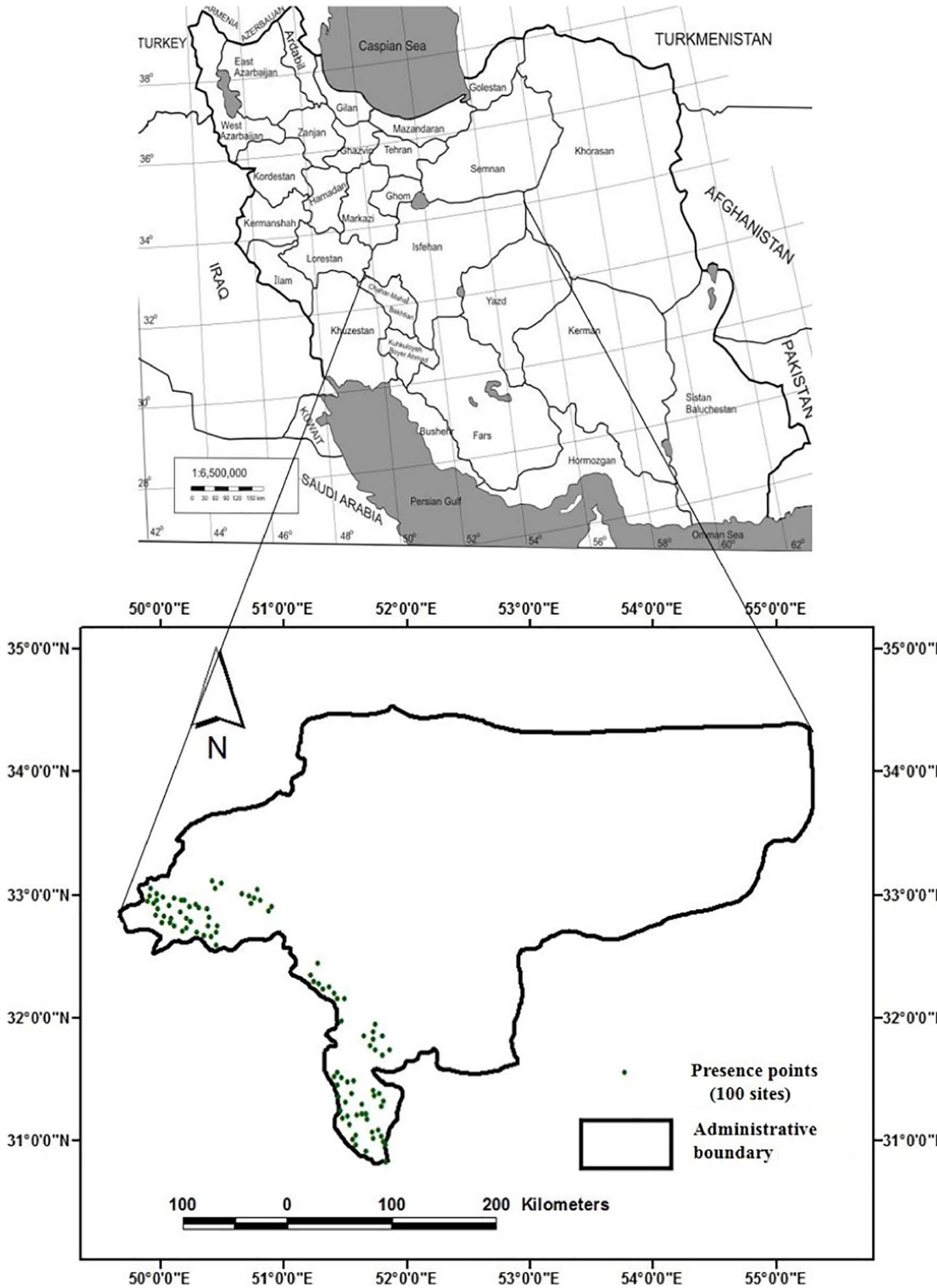

Fig. 2. The location of 100 species occurrence sites in Isfahan province- Iran.

features were selected in the modeling process. The produced model was assessed by calculating the area under the curve (AUC) of the receiver operating characteristic (ROC) plot (Phillips et al., 2006). The AUC is a measure of model performance and varies from 0 to 1. A value of 1.0 indicates perfect discrimination (Fielding and Bell, 1997). The jackknife procedure was applied to evaluate the importance of the variables (Yang et al., 2013). This process shows the training gain of each variable if the model was run in isolation compared with the training gain with all variables. Species response curves were produced to explore the relationships between the habitat suitability of target

Table 1
Environmental variables used in species distribution modeling process. The most important environmental variables are highlighted in bold. The permutation importance is calculated for each environmental variable in turn, "the values of that variable on training presence and background data are randomly permuted. The model is re-evaluated on the permuted data, and the resulting drop in training AUC is shown in the table, normalized to percentages. A large decrease AUC indicates that the model depends heavily on that variable" (Phillips, 2006).

Variable code	Variable type	Unit	Percent contribution	Permutation importance
Bio1	Annual mean temperature	°C		
Bio2	**Mean diurnal range (mean of monthly** max. **and** min. **temp.)**	**°C**	**7.3**	**2.4**
Bio3	**Isothermally ((Bio2/Bio7) × 100)**	–	**1.2**	**1**
Bio4	**Temperature seasonality (standard deviation × 100)**	**(coeff. of variation °C)**	**0.1**	**0**
Bio5	**Maximum temperature of warmest month**	**°C**	**1.1**	**4.8**
Bio6	Minimum temperature of coldest month	°C		
Bio7	Temperature annual range (Bio5–Bio6)	°C		
Bio8	**Mean temperature of wettest quarter**	**°C**	**1.4**	**4.7**
Bio9	Mean temperature of driest quarter	°C		
Bio10	Mean temperature of warmest quarter	°C		
Bio11	Mean temperature of coldest quarter	°C		
Bio12	**Annual precipitation**	**mm**	**13.2**	**7.9**
Bio13	Precipitation of wettest period	mm		
Bio14	**Precipitation of driest period**	**mm**	**8.3**	**2.7**
Bio15	**Precipitation seasonality (CV)**	**(coeff. of variation; percent)**	**0**	**0.2**
Bio16	Precipitation of wettest quarter	mm		
Bio17	Precipitation of driest quarter	mm		
Bio18	**Precipitation of warmest quarter**	**mm**	**19.2**	**4.3**
Bio19	**Precipitation of coldest quarter**	**mm**	**39.2**	**66.2**
ELE	**Elevation**	**m**	**9.9**	**5.5**
SLO	**Slope**	**percent**	**0.1**	**0.3**
ASP	**Aspect**	**degree**	**0**	**0**

species and environmental variables. The produced potential species distribution map had a range of values between 0 and 1. These values were regrouped into four classes of potential habitats with high potential (> 0.6), good potential (0.4–0.6), moderate potential (0.2–0.4), and low potential (< 0.2) (Yang et al., 2013).

3. Results

According to the obtained AUC (0.95), MaxEnt had better performance compared to the random model. The model output provided satisfactory results with both training and test data sets. Four variables, including precipitation of coldest quarter (Bio19), annual precipitation (Bio12), precipitation of warmest quarter (Bio18), and elevation had > 80% contribution to the model. Precipitation of coldest quarter (Bio19) explained 39.2% of the total variance and was thus identified as the main factor affecting the spatial distribution of *D. mucronata* (Table 1).

The jackknife test showed that *D. mucronata* distribution was largely affected by elevation, annual precipitation (Bio12), precipitation of coldest quarter (Bio19), precipitation of warmest quarter (Bio18), minimum temperature of warmest month (Bio5), and mean temperature of warmest quarter (Bio8) (Fig. 3). Species response curves represent the relationships between environmental factors and the species occurrence probability. They demonstrate biological tolerances and habitat preferences for target species. According to the obtained response curves of the species, *D. mucronata* prefers habitats with mean precipitation of coldest quarter from 120 to 140 mm, annual precipitation of 240–280 mm, and elevation > 2600 m above sea level (Fig. 4). The band-like response curves show uncertainties and come from randomness of several runs. The response curves of the species indicated that precipitation of coldest quarter and annual precipitation followed a Gaussian shape and precipitation of warmest quarter and elevation had a sigmoid trend. The optimum ranges of Bio19 and Bio12 were 100–150 mm and 200–300 mm, respectively (Fig. 4).

Species distribution maps showed that 14.9%, 9.8%, and 2.1% of the study area were recognized as high potential habitats of *D. mucronata* in the current condition, 2030, and 2080 projections, respectively (Table 3 and Fig. 5). The averaged future predictions of MaxEnt for 2030 and 2080 (A2a emission scenario) revealed a reduction in suitable habitats of *D. mucronata* in more elevated sites of the western and southern parts of Isfahan. The map obtained from MaxEnt was compared with elevation range classes and it indicates that the species distribution would not considerably change in elevations > 3000 m above sea level, because the appropriate climatic envelope (precipitation and temperature condition) of the species will become unsuitable under climate change (Figs. 6 & 7).

4. Discussion

After removing auto-correlated parameters (Tables 1 and 2), MaxEnt indicated that the current *D. mucronata* distribution was more influenced by two precipitation variables (Bio19 and Bio12), elevation, and two temperature variables (Bio8 and Bio5). Precipitation played a key role in determining the distribution of potential habitats of *D. mucronata* in its native range. Areas with higher elevation (> 3000 m above sea level) and precipitation (> 400 mm) are unsuitable habitats for *D. mucronata*. When the habitats turn completely unsuitable for the occurrence of *D. mucronata*, other competitive species (e.g. *Quercus persica*) will become dominant in the area. According to the obtained response curves, this species is adapted to cold temperature conditions, i.e. Bio5 < 35 °C and Bio8 < 15 °C.

Model projection under HadCM3 climate change scenario on the distribution of vulnerable species of *D. mucronata* suggested that this species would lose its optimum range of occurrence and that its

Table 2
Correlation matrix among environmental variables.

	Bio1	Bio2	Bio3	Bio4	Bio5	Bio6	Bio7	Bio8	Bio9	Bio10	Bio11	Bio12	Bio13	Bio14	Bio15	Bio16	Bio17	Bio18	Bio19	ELE	SLO	ASP
Bio1	1																					
Bio2	0.999	1																				
Bio3	0.003	0.021	1																			
Bio4	0.149	0.153	0.033	1																		
Bio5	0.608	0.609	0.142	0.160	1																	
Bio6	0.991	0.992	0.021	0.148	0.601	1																
Bio7	0.970	0.972	0.020	0.084	0.568	0.963	1															
Bio8	0.771	0.772	− 0.012	0.108	0.576	0.766	0.753	1														
Bio9	0.999	1.000	0.021	0.150	0.612	0.992	0.971	0.773	1													
Bio10	0.998	0.999	0.022	0.152	0.612	0.992	0.969	0.772	1.000	1												
Bio11	0.761	0.761	− 0.023	0.107	0.575	0.758	0.745	0.985	0.763	0.762	1											
Bio12	− 0.157	− 0.151	0.241	− 0.121	0.119	− 0.151	− 0.179	− 0.167	− 0.152	− 0.154	− 0172	1										
Bio13	− 0.127	− 0.130	− 0.061	− 0.065	− 0.043	− 0.115	− 0.154	− 0.144	− 0.128	− 0.127	− 0.125	0.294	1									
Bio14	0.098	0.097	− 0.011	0.094	0.058	0.092	0.092	0.094	0.098	0.100	0.102	0.062	0.140	1								
Bio15	0.028	0.016	− 0.102	0.067	0.139	0.023	− 0.000	− 0.058	0.015	0.018	− 0.036	− 0.138	− 0.134	0.022	1							
Bio16	− 0.200	− 0.204	− 0.058	− 0.019	− 0.121	− 0.182	− 0.224	− 0.219	− 0.201	− 0.200	− 0.193	0.354	0.882	0.159	− 0.108	1						
Bio17	− 0.009	− 0.017	− 0.208	0.281	− 0.217	− 0.006	− 0.057	0.024	− 0.020	− 0.020	0.011	0.054	− 0.022	0.130	− 0.031	0.103	1					
Bio18	0.004	0.001	− 0.207	0.278	− 0.172	0.013	− 0.046	0.051	− 0.002	− 0.002	0.034	0.059	− 0.006	0.142	− 0.051	0.118	0.954	1				
Bio19	− 0.179	− 0.182	− 0.052	− 0.000	− 0.060	− 0.158	− 0.198	− 0.193	− 0.179	− 0.179	− 0.173	0.329	0.836	0.172	− 0.129	0.928	0.129	0.140	1			
ELE	− 0.481	− 0.489	− 0.051	− 0.254	− 0.142	− 0.496	− 0.495	− 0.355	− 0.485	− 0.485	− 0.348	0.007	0.173	− 0.089	− 0.079	0.169	− 0.114	− 0.103	0.149	1		
SLO	− 0.172	− 0.156	0.194	0.025	− 0.172	− 0.144	− 0.139	− 0.173	− 0.162	− 0.164	− 0.194	0.050	0.007	0.120	− 0.143	0.052	− 0.023	− 0.018	0.088	− 0.001	1	
ASP	0.080	0.004	0.004	− 0.001	0.011	0.070	0.001	0.002	0.009	0.009	0.007	− 0.061	− 0.060	− 0.060	0.010	− 0.006	− 0.008	− 0.006	− 0.004	0.015	0.020	1

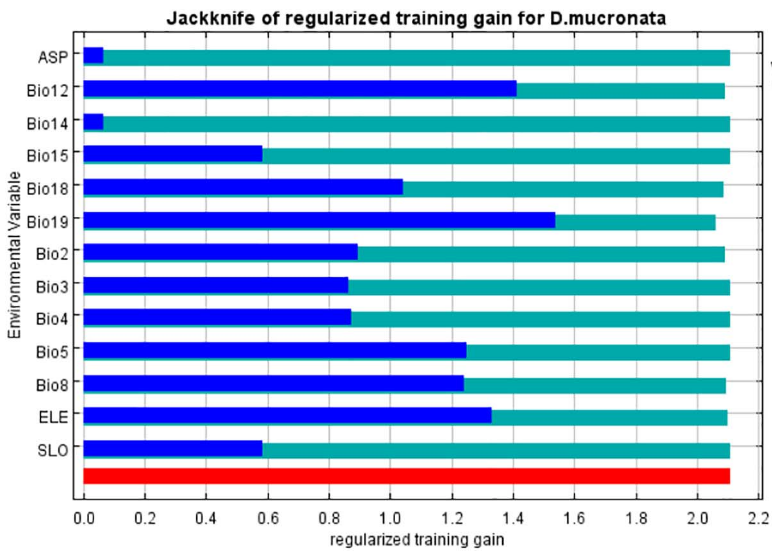

Fig. 3. Relative predictive power of different environmental variables based on the jackknife of regularized training gain in MaxEnt models for *D. mucronata Royle.*

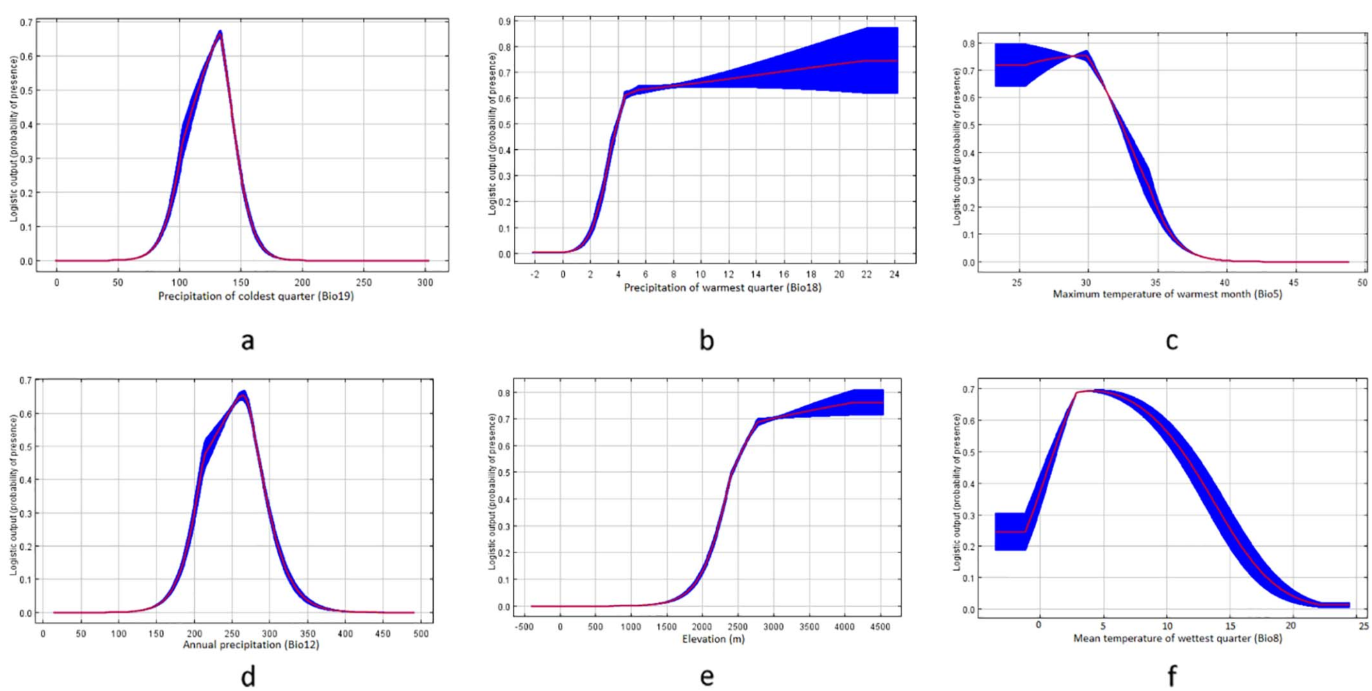

Fig. 4. *D. mucronata* response curves in relation to (a) precipitation of coldest quarter- Bio19, (b) precipitation of warmest quarter- Bio18, (c) Minimum temperature of warmest month- Bio5, (d) annual precipitation- Bio12, (e) elevation, and (f) mean temperature of warmest quarter- Bio8.

Table 3
The areas of each potential habitat class using MaxEnt under current and future climatic conditions.

Habitat suitability classes	Area percent (current)	Area percent (2030)	Area percent (2080)
Least potential (< 0.2)	78.4	80.6	83.1
Moderate potential (0.2–0.4)	1.9	2.5	7.6
Good potential (0.4–0.6)	4.8	7.1	7.2
High potential (> 0.6)	14.9	9.8	2.1

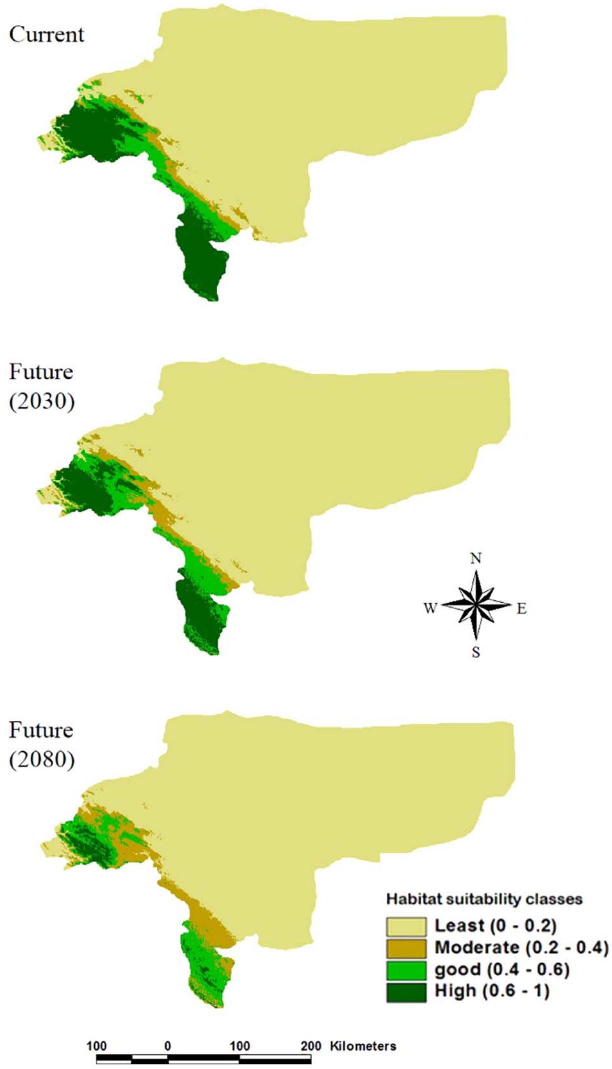

Fig. 5. Species distribution maps of *Daphne mucronata Royle* under current and future climatic change condition (2030 and 2080) based on A2a/HadCM3 scenario.

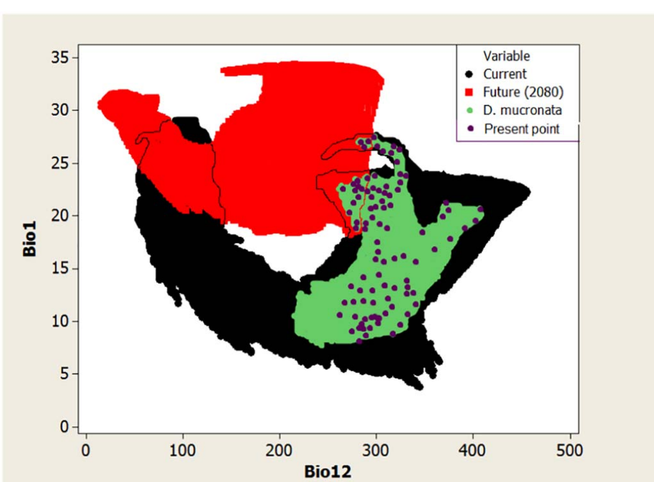

Fig. 6. Scatter plot of climatic niche (Bio1 = mean annual temperature, Bio12 = annual precipitation) of the species under current and future condition (2080).

geographic domains would shrink under climate warming projection. Comparing the map obtained from MaxEnt with elevation range classes revealed that the distribution of *D. mucronata* would not considerably change in elevations > 3000 m above sea level. The most drastic change in species distribution would occur in sites located at 2000–3000 m above sea level. This species would disappear in sites located below 2000 m. The reason for this habitat shift is the fact that the climatic niche of the species (temperature and precipitation) became totally inappropriate for regeneration and maintained species in lower elevation ranges (Fig. 6).

Although watershed management practices, such as constructing counter furrows and pitting, will increase soil moisture and infiltration and fulfill moisture requirements to support species occurrence, mangers have no control over species temperature envelope. There are some other instances of species adaptation strategies such as migration to higher elevation ranges and seed dispersal mobility (Midgley et al., 2006; Neilson et al., 2005). In this study, *D. mucronata* showed range expansions towards higher elevation ranges (Fig. 7.). Such expansions can be facilitated through adaptations if new sites meet the soil requirements of the species. Moiseev and Shiyatov (2003) reported a similar upward shift of tree line under climate change in Siberia and in the Alpine Mountains in Switzerland (Pauli et al., 1996).

Due to their specific phenological or physiological characteristics, species with wide ecological niche can benefit from future climatic conditions. Meanwhile, species with limited geographical distribution are more threatened (Khanum et al., 2013; Westoby and Burgman, 2006). *D. mucronata* is known as a transitional species that occurs in the ecotone area between semi-Steppe rangelands and arid forests in Zagros mountain range. This species may facilitate the growth and development of some other grass and herb species. Their canopy cover provides a microhabitat that is more appropriate for seed germination and seeding recruitment than its surrounding environment (Ren et al., 2002). Therefore, climate change not only threatens *D. mucronata* distribution, but also affects other co-occurring species.

Since MaxEnt utilizes bioclimatic variables to map the fundamental niche (different from occupied or realized niche) of the species, it may over-predict the suitable habitat for *D. mucronata* in some areas (Murienne et al., 2009; Pearson, 2007). The realized niche of species is a subset of the fundamental niche that it actually occupies (Hutchinson, 1957). Geographical barriers, human disturbances (e.g. modification of rangelands for dry farming), or associated competitive species may limit the fundamental niche of species. Because of severe modifications in the *D. mucronata* habitat, land use changes, and grazing, the species' habitat is already very fragmented. Therefore, further climate changes may lead to the extinction of this species.

5. Conclusion

Modeling can provide powerful decisive tools for conservation planners. We used a machine learning method (MaxEnt) to model the current and future distribution of *D. mucronata*. This study indicated that the domain distribution of this species would shift to higher elevation ranges. Moreover, its habitat in areas lower than 2000 m above sea level will become totally inappropriate and the species will disappear in these areas. In the future, the species occurrence would fluctuate in areas between 2000 and 3000 m above sea level. Therefore, restoration ecology should focus on the identification and achievement of realistic goals that would allow vulnerable and endangered species (such as *D. mucronata*) to adapt to new environmental conditions. This information can be also used for protecting susceptible habitats from the impacts of climate change and future modifications. It would also be necessary for conservation planners and rangeland managers trying to protect the species from extinction.

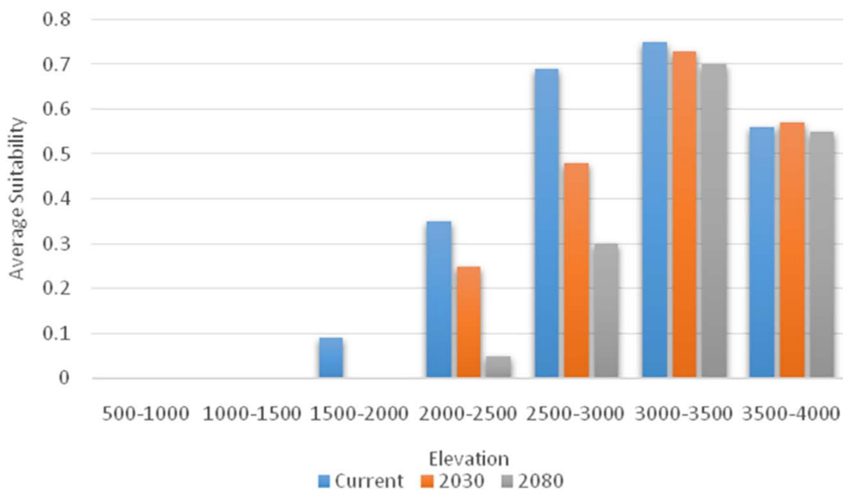

Fig. 7. Habitat suitability shifts of *D. mucronata* in relation to elevation under current and future climate change scenarios.

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